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MODIS 250M Burnt Area Detection Algorithm:

A Case Study Applied, Optimized and Evaluated over Continental Portugal.

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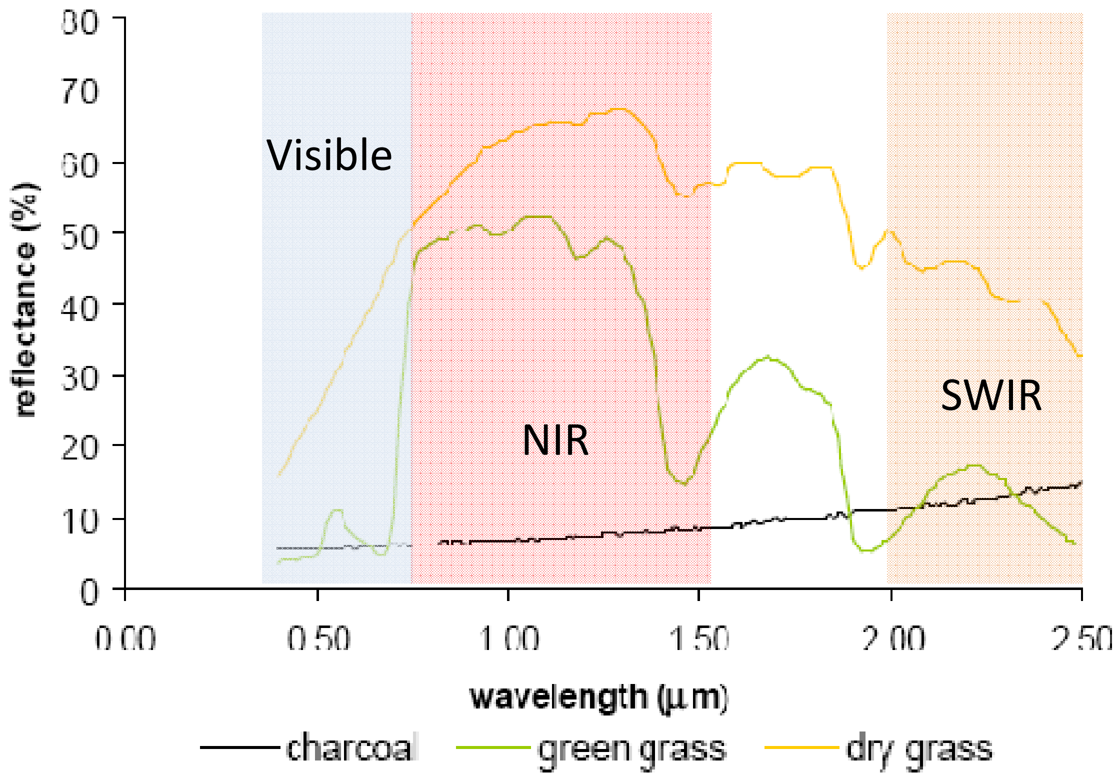
Background

•**Burned area (BA)** analysis is based on detecting the char/ash/scar signals, if preceded by vegetation, the change highlights a fire event

•Compared with the **VISIBLE** (0.4-0.7 μm) and the **SWIR** (2.0-2.5 μm) the **NIR** is, unquestionably, the best spectral region to **discriminate** between burned areas and other surfaces, such as vegetation and not-too-dark soils. NIR reflectance can only decrease.



MODIS sensor spectral bands (1-19)

Band	Wavelength (nm)	Resolution (m)	Primary Use
1	620–670	250	Land/Cloud/Aerosols Boundaries
2	**841–876**	**250**	
3	459–479	500	Land/Cloud/Aerosols Properties
4	545–565	500	
5	1230–1250	500	
6	1628–1652	500	
7	2105–2155	500	
8	405–420	1000	Ocean Color/ Phytoplankton/ Biogeochemistry
9	438–448	1000	
10	483–493	1000	
11	526–536	1000	
12	546–556	1000	
13	662–672	1000	
14	673–683	1000	
15	743–753	1000	
16	862–877	1000	
17	890–920	1000	Atmospheric Water Vapor
18	931–941	1000	
19	915–965	1000	

... and more 16.

Band 2 used for BA detection

- The algorithm presented is a spin-off of one of classification algorithms developed for VGT and AATSR under the FIRE-CCI project.
- The algorithm was already applied to the South American tropical forest (EGU 2013 poster)

Aim

Develop a BA detection algorithm for NIR imagery captured by satellites with high frequency of observation.

Objective

Adjust and optimize the BA algorithm to MODIS 250 m^2 imagery for continental Portugal for the period (2001-2013).

Overview

1. Did a significant and persistent drop in reflectance occur at a given pixel ?

Spectral analysis

Score changes when and how.

→ Change detection algorithm

2. Did it occur in the right time of the year?

Temporal revision

Compare with known fire seasonality to separate other from source of change.

→ Prob. LUT of Scores vs. Fire seasonality

3. Is it coherent with its surroundings?

Spatial revision

Look for evidence for similar changes in the nearby pixels.

→ MRF segmentation dates & probabilities

Data

- **MODIS 250 m^2 (MOD09DQ) daily NIR band (2) images for tiles covering continental Portugal (h17v04 and h17v05) for the period 2001-2013 – input to the algorithm**

- **MOD09DA cloud mask layer information available from the 500 m^2 reflectance daily images (2001-2013) – cloud screening.**

- **Fire Activity Distribution (0.5º) based on adjustments made** with von Mises distributions to active fire counts(Benali *et al.* 2012) **– penalize off-season events.**

- **Landsat derived BA binary maps at 30 m^2 (2001-2009) – parameter optimization and accuracy assessment.**

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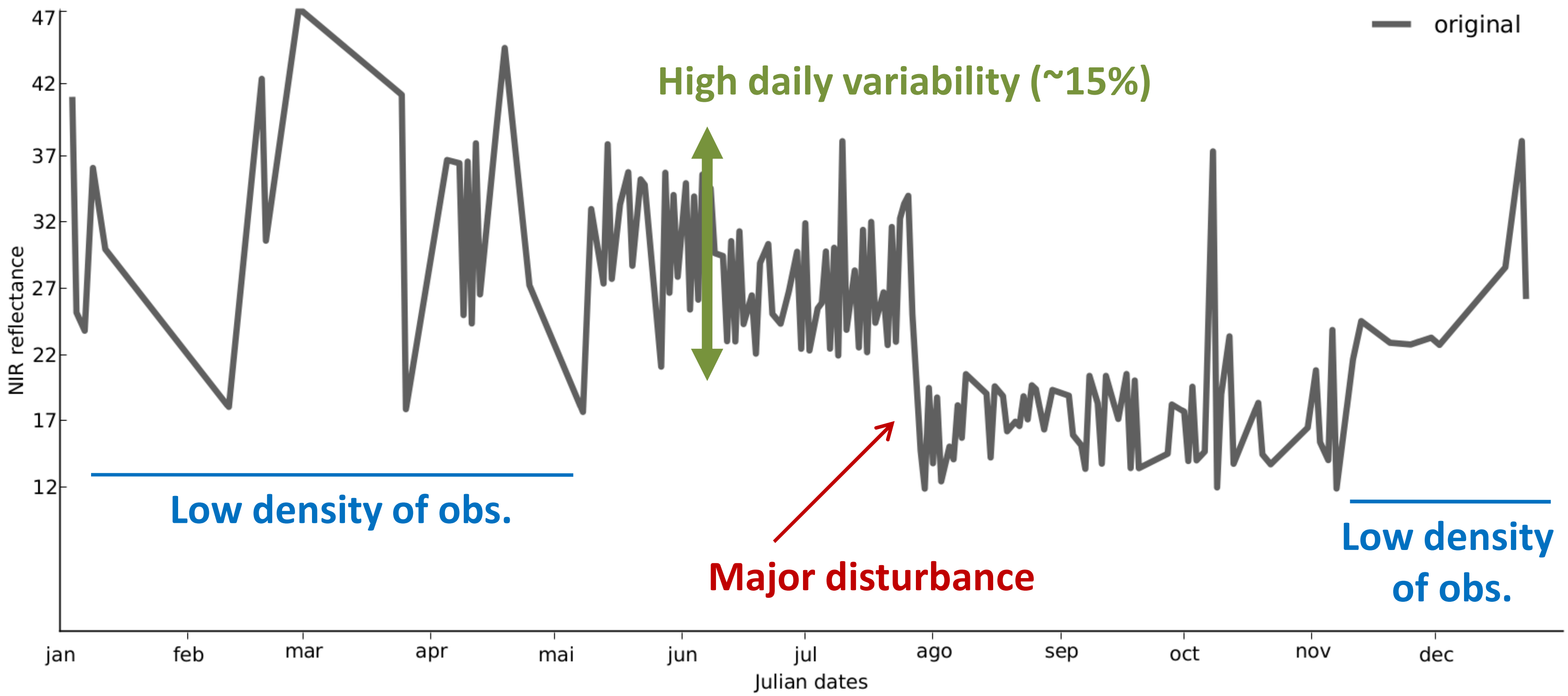
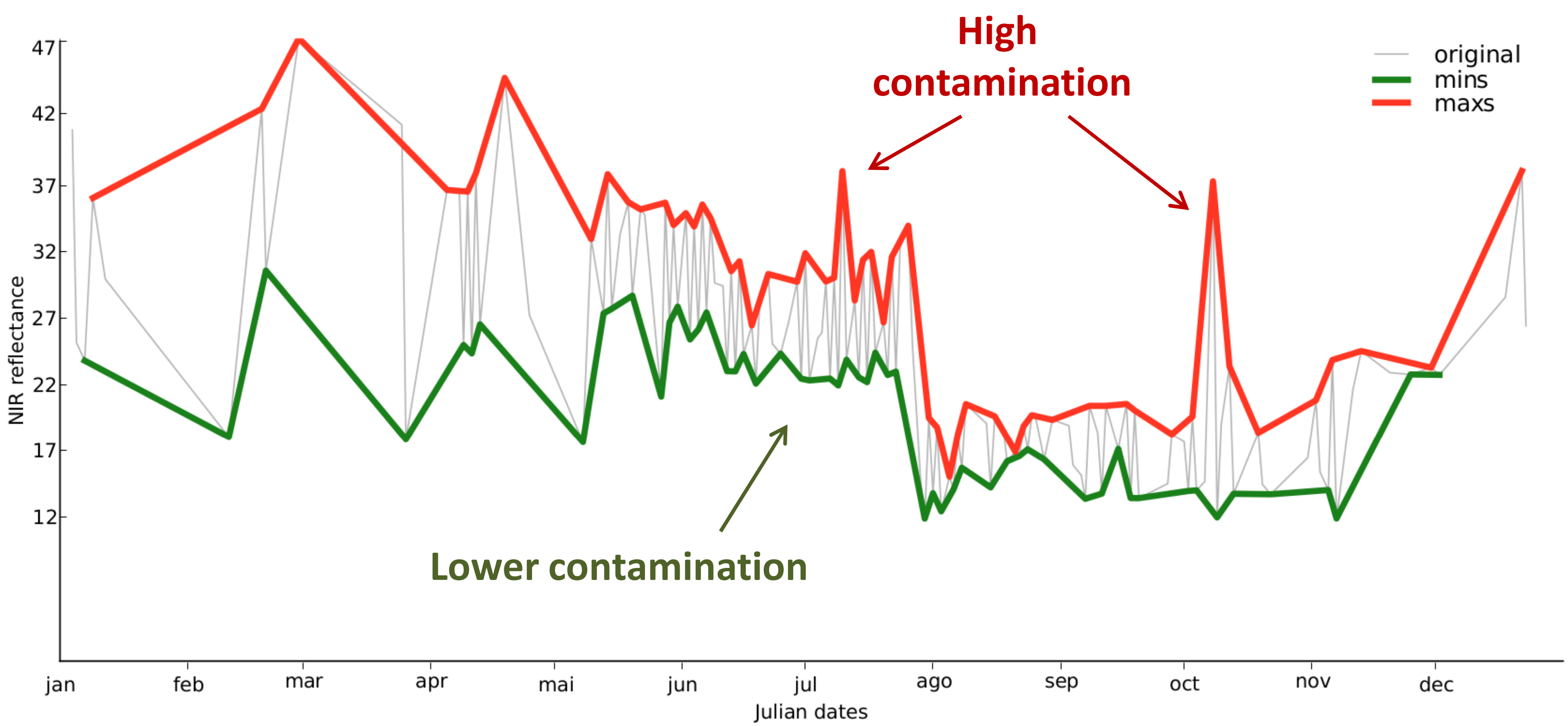
Time-series analysis



Time-series of the NIR reflectance for a pixel located in the centre of Portugal over forest for year 2005.

Time-series analysis - Construct a series of ρNIR minima



Determine the upper and lower envelopes of time series. Oscillation maxima are "noisier", affected by residual atmospheric contamination.

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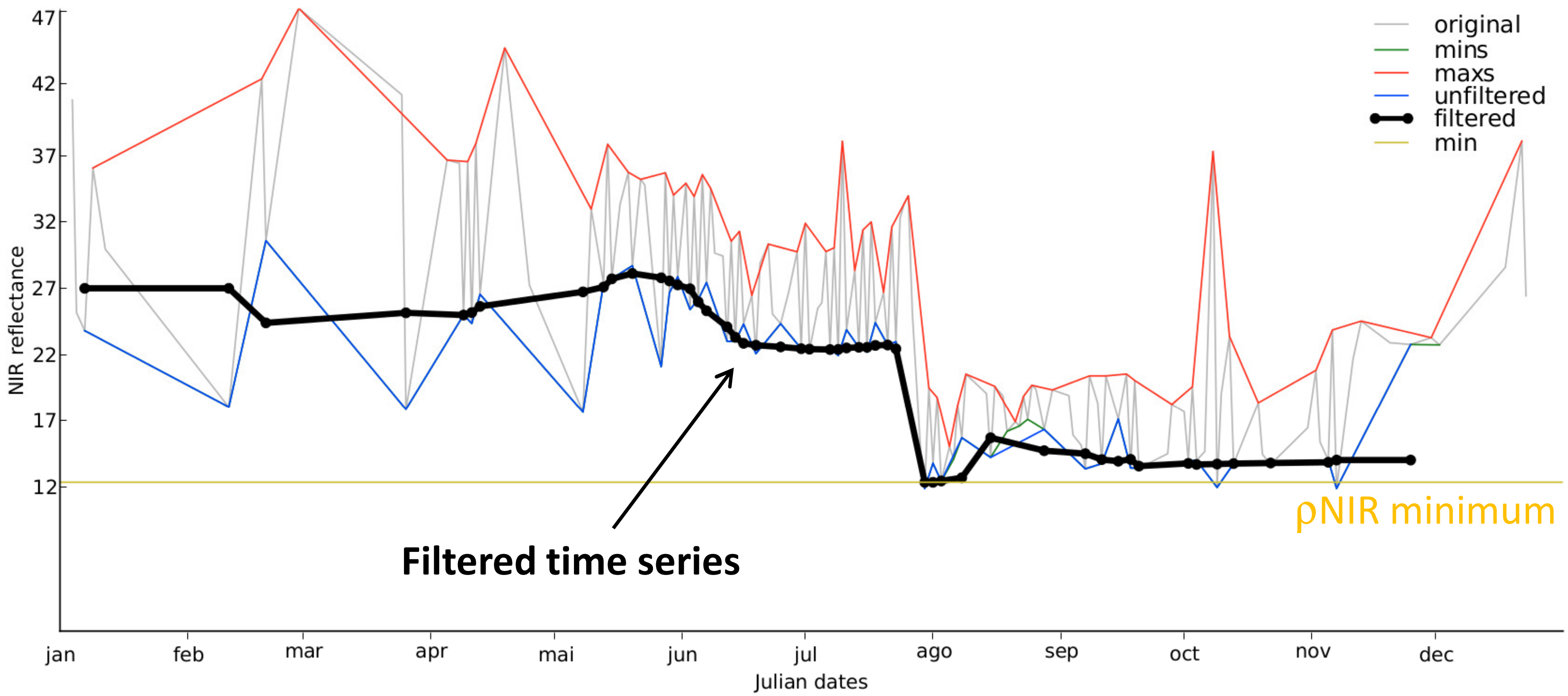
Time-series analysis – Robust filtering



•**Robust filtering** of minima time series, to remove **cloud shadow** spikes in ρNIR.

•Determine the absolute **minimum** refectance of the time-series.

$$\min\{y_i\}_{i=1:n}$$

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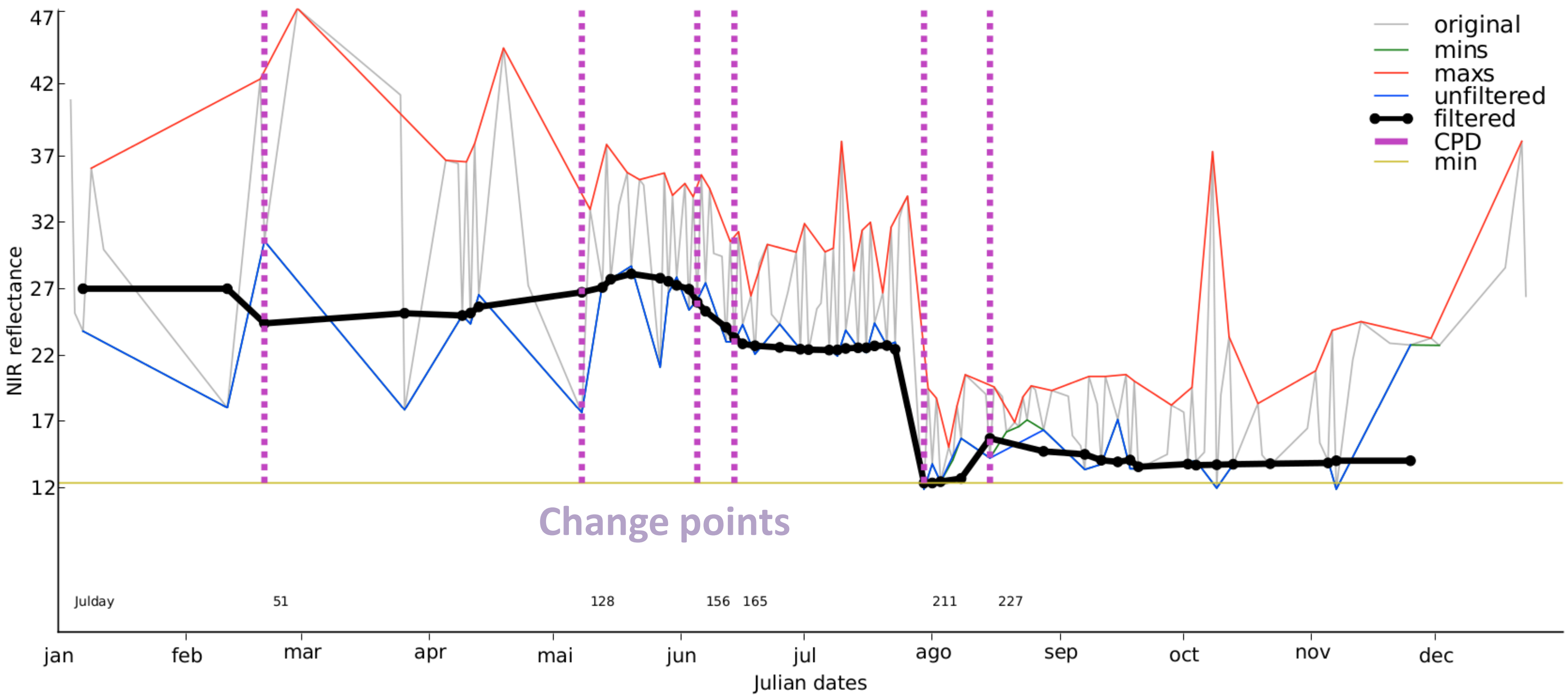
Time-series analysis – Change detection



Change points are those points in time which divide a data set into distinct homogeneous segments.

Pruned Exact Linear Time (PELT): changes in mean ρNIR, assuming it follows Normal distribution with constant variance and changing mean (Killick *et al*,. 2012).

Time-series analysis – Change point scoring

CP scores represent the "likelihood" of corresponding to a perturbation event. The score magnitude at a given CP is determined by the ratio between ρNIR drop and its potential drop.

$$\frac{\overline{S}_i - \overline{S}_{i+1}}{\overline{S}_i - K}$$

where

$\overline{S}_{i+1}$ is the mean ρNIR of the post-CP time segment

$\overline{S}_i$ is the mean ρNIR of the pre-CP time segment

M is $\min\{y_i\}_{i=1:n}$

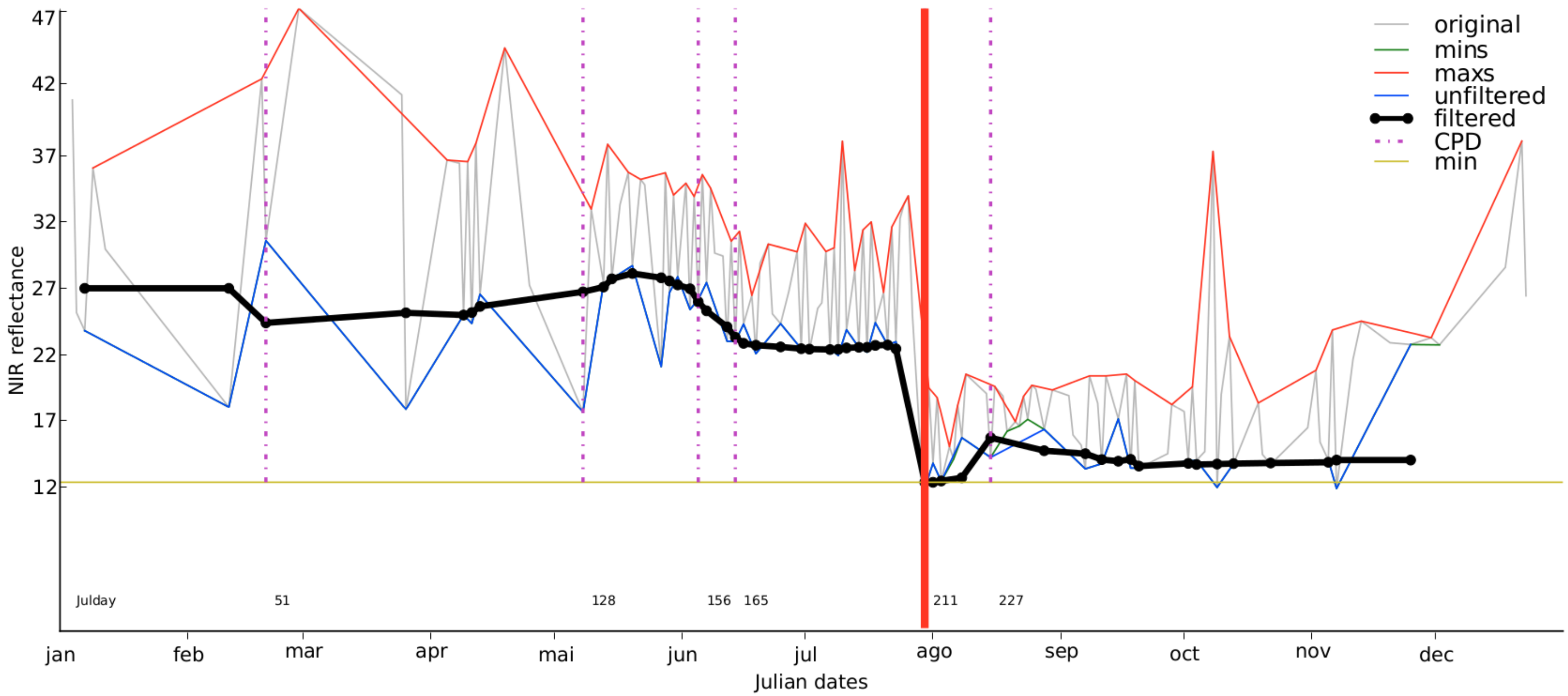
K is $0.8 * M \Rightarrow M < 0.2$

$0.8 * 0.2 = 0.16 \Rightarrow M \geq 0.2$

factor to allow better discrimination post-change ρNIR = minimum ρ value.

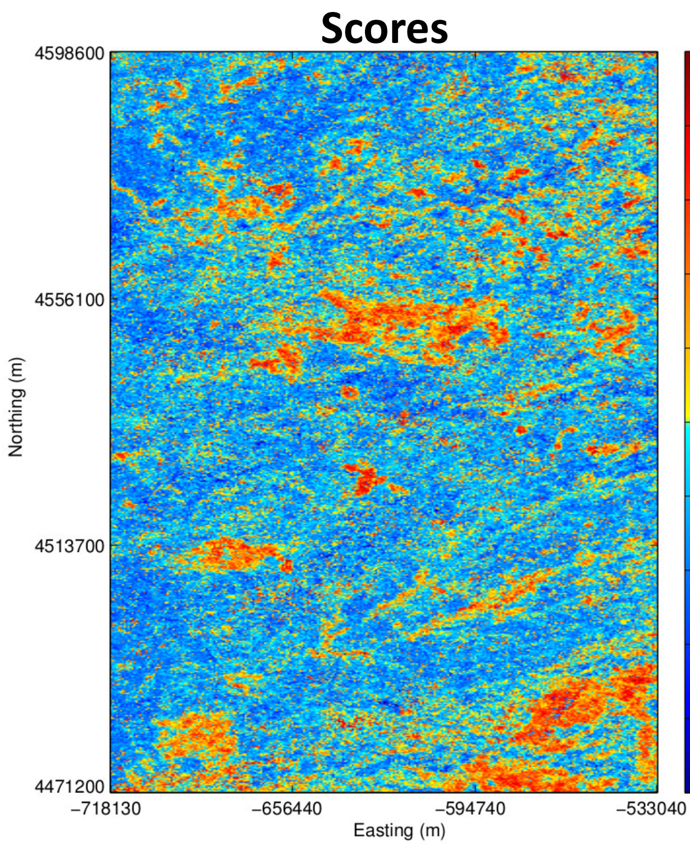
increases the spectral difference between post-change reflectance and the time series minimum

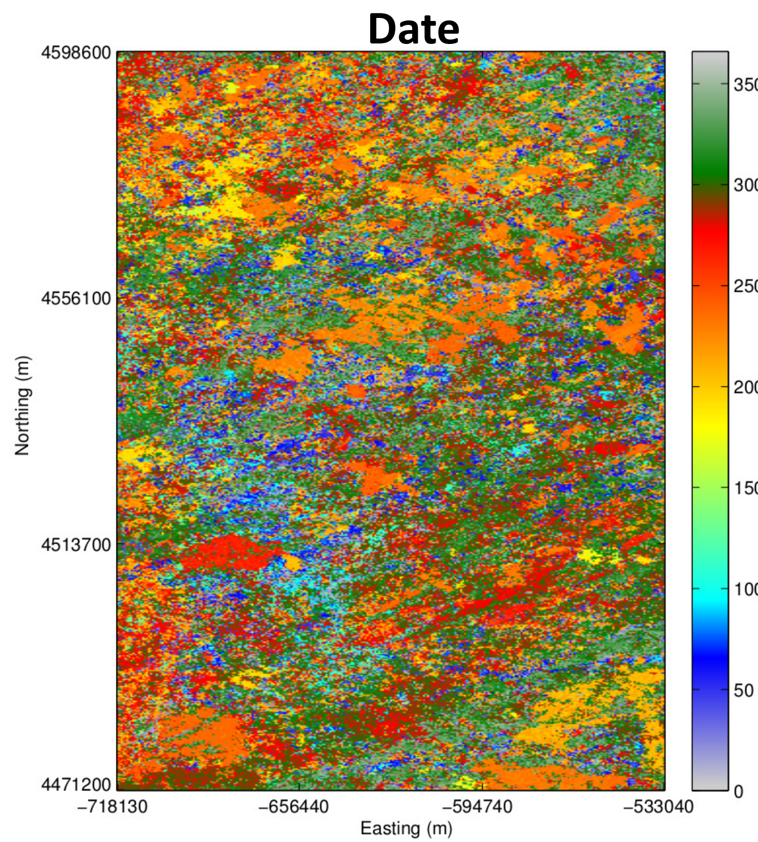
Time-series analysis – Select CP



Form all change points that are associated with a decrease select the one with the highest score. It represents the biggest distrunbance leading to lower reflectance.

Time-series analysis – Outputs

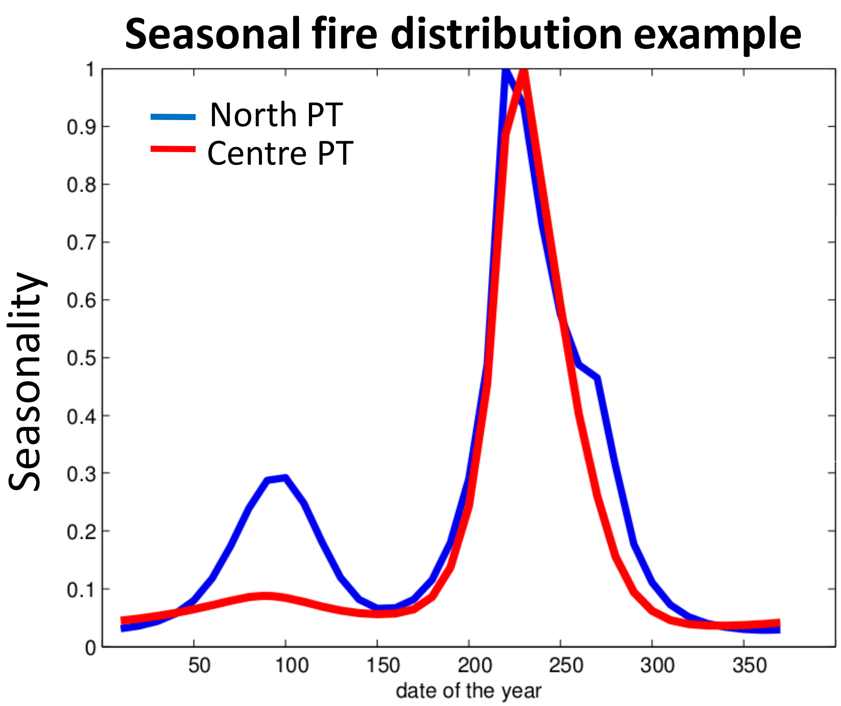


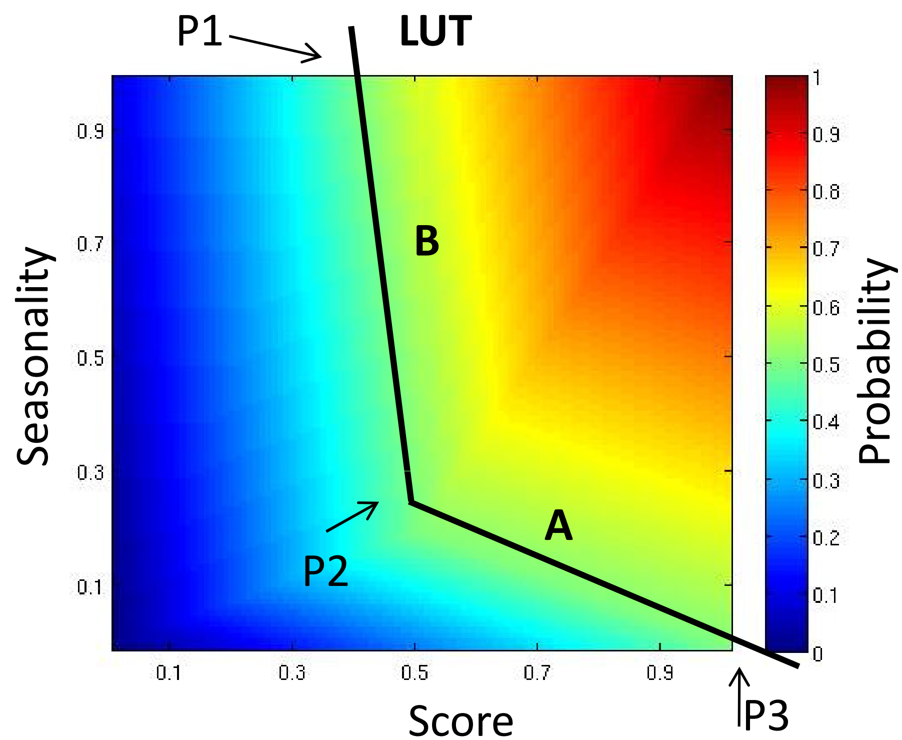


NIR pertubations due to vegetation removal may also result from other causes: harvesting, grazing, windthrow, or defoliation by plant pests and diseases.

CP score and associated date will serve as imputs to the temporal revison

Temporal revision





The conversion of pertubations into "probabilities" takes into account the date of the year and the magnitude of the scores.
LUT probability surface is defined assuming 2 types of score vs. Seasonality relations: Off fire-season (A) and during fire-season (B) and is generated from 3 parameters (P1, P2, P3). Rate of change is defined by a logit function (P4, P5).

Spatial revision

- The last processing step is to **classify the pixels** taking into account the **spatial** and **temporal** relations between them.

- The solution is one that solves the maximum a posteriori – Markov random field (MAP-MRF) problem by determining the **max. flow/min. source-sink cut** in a graph, where the source is the vertex **"unburned"** and the sink is the vertex **"burned"**.

- This partition gives the segmentation of the image into unburned and burned pixels.

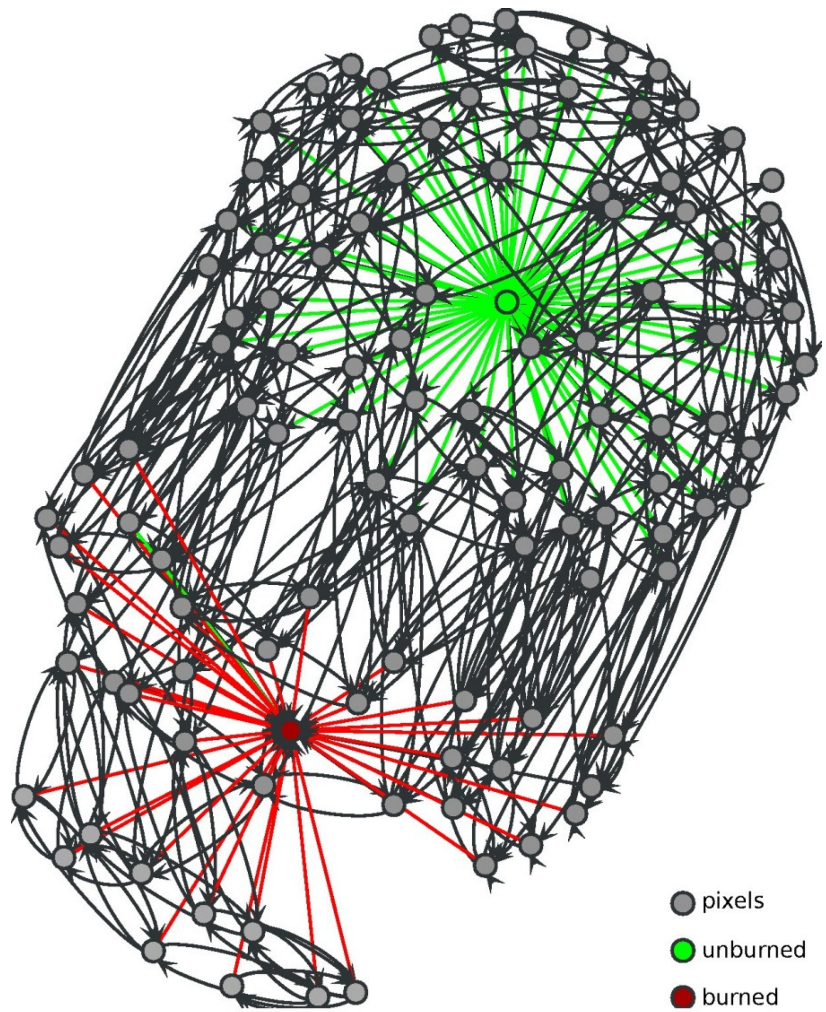
Spatial revision

Vertex are the pixels that have edges:

1. connecting to **"unburned"** or **"burned"** with length defined by the burnt probability. Decision to which made by a **threshold (Tr).**

2. connecting surrounding pixels with length defined by the day difference over a maximum allowed **(Dmax).**

10 x 10 pixel representation



I – Background

II – Overview

III – Data

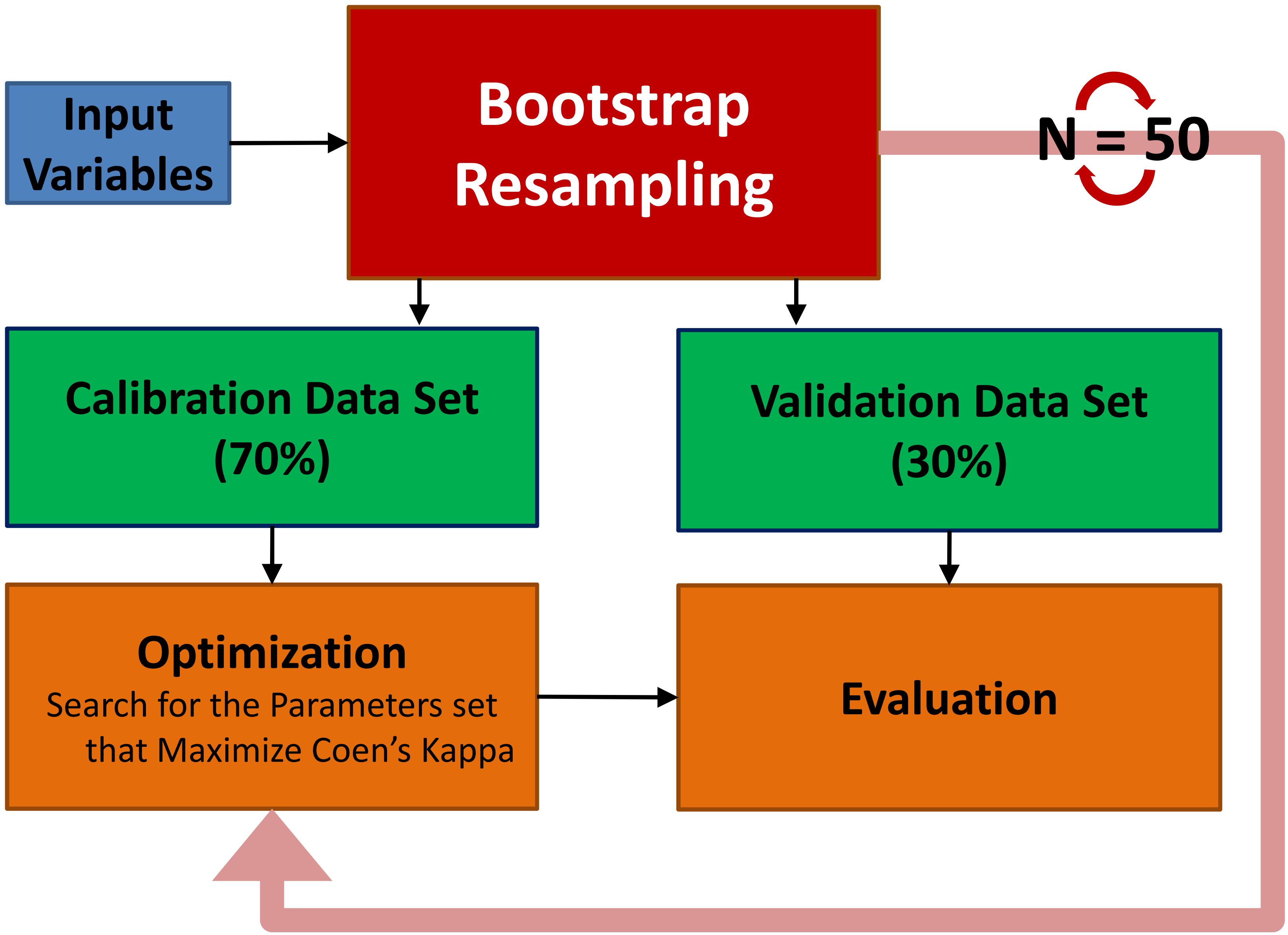
IV – Algorithm

V – Optimization

VI – Results

VII – Discussion

Optimization Scheme



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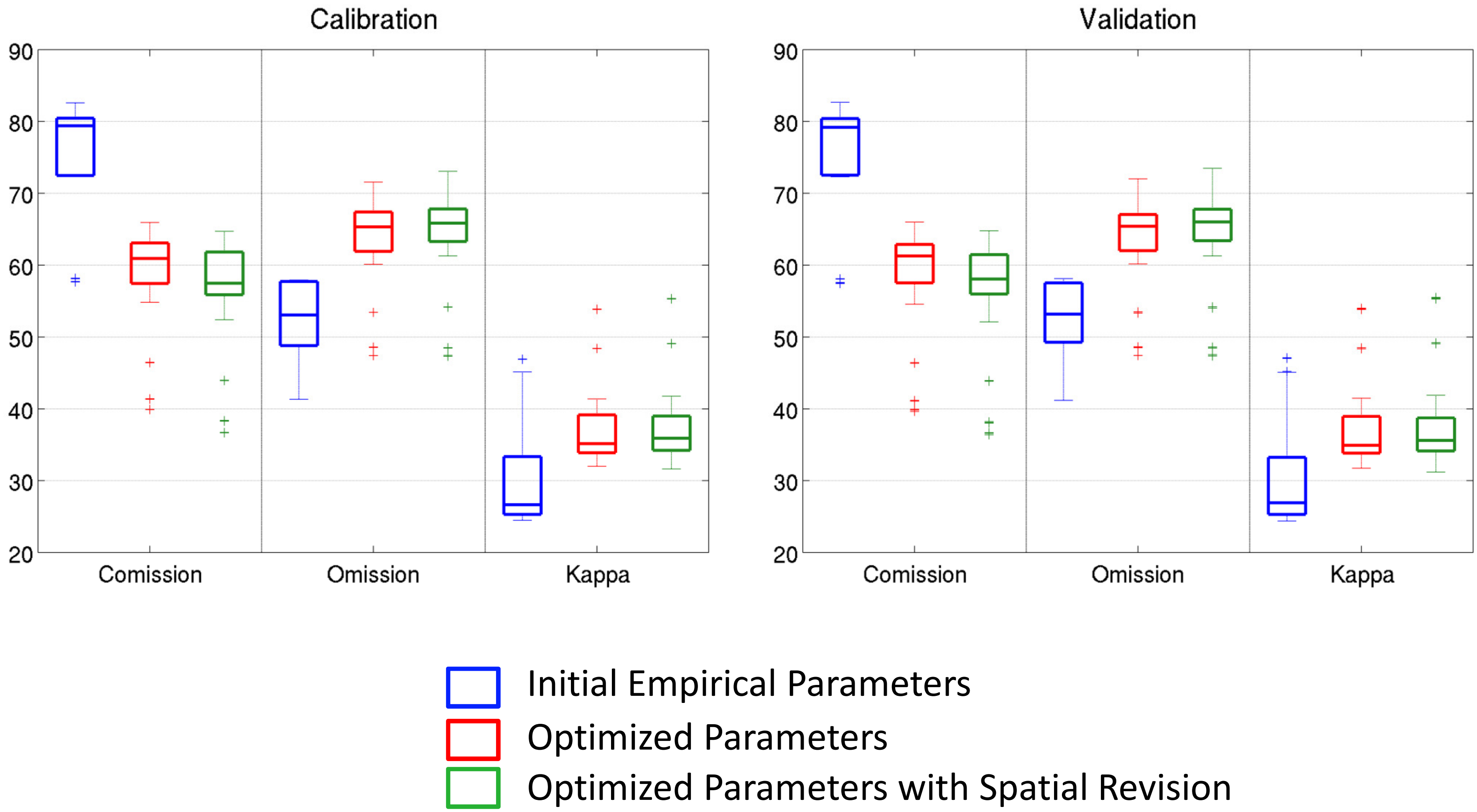
Algorithm Performance



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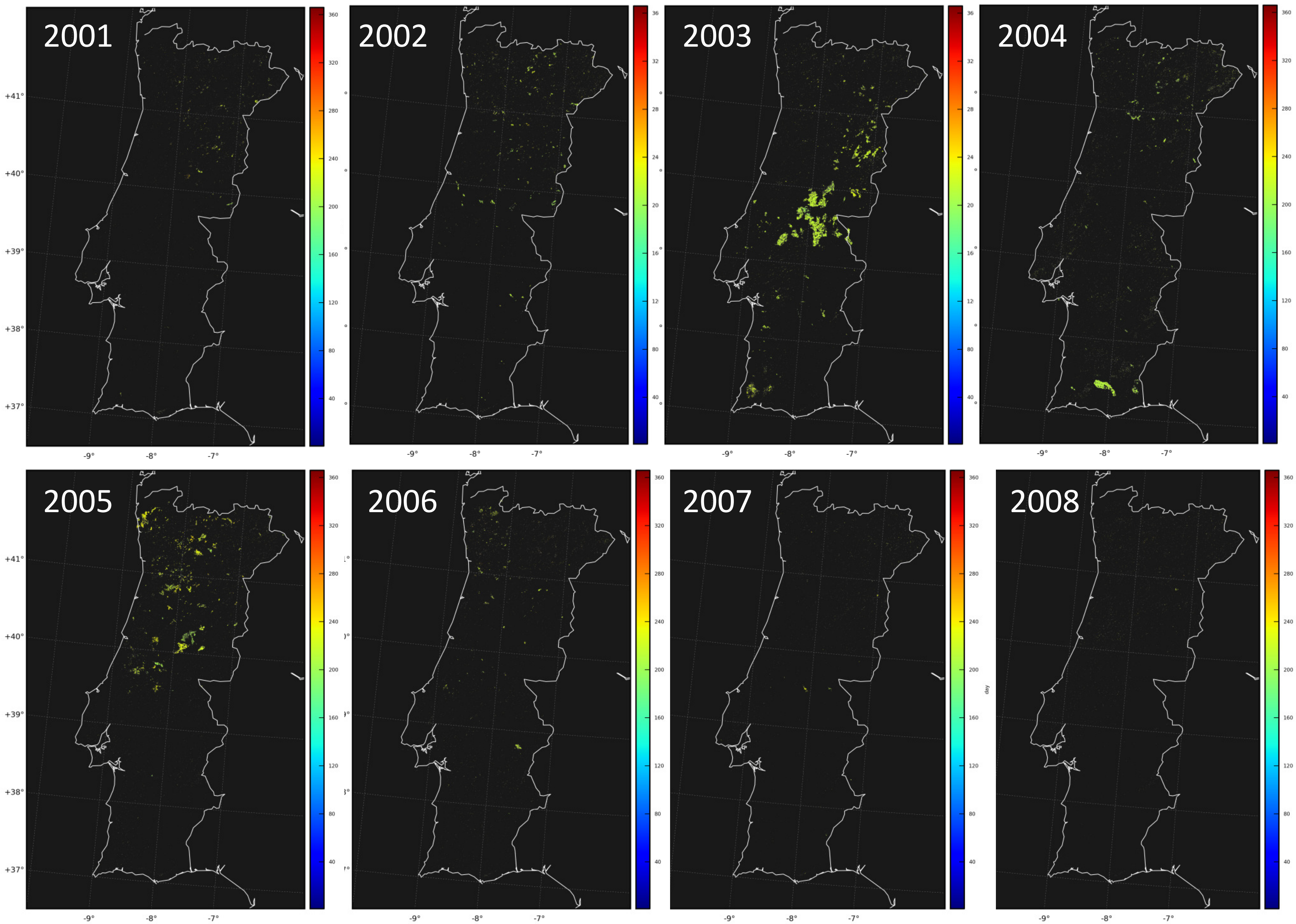

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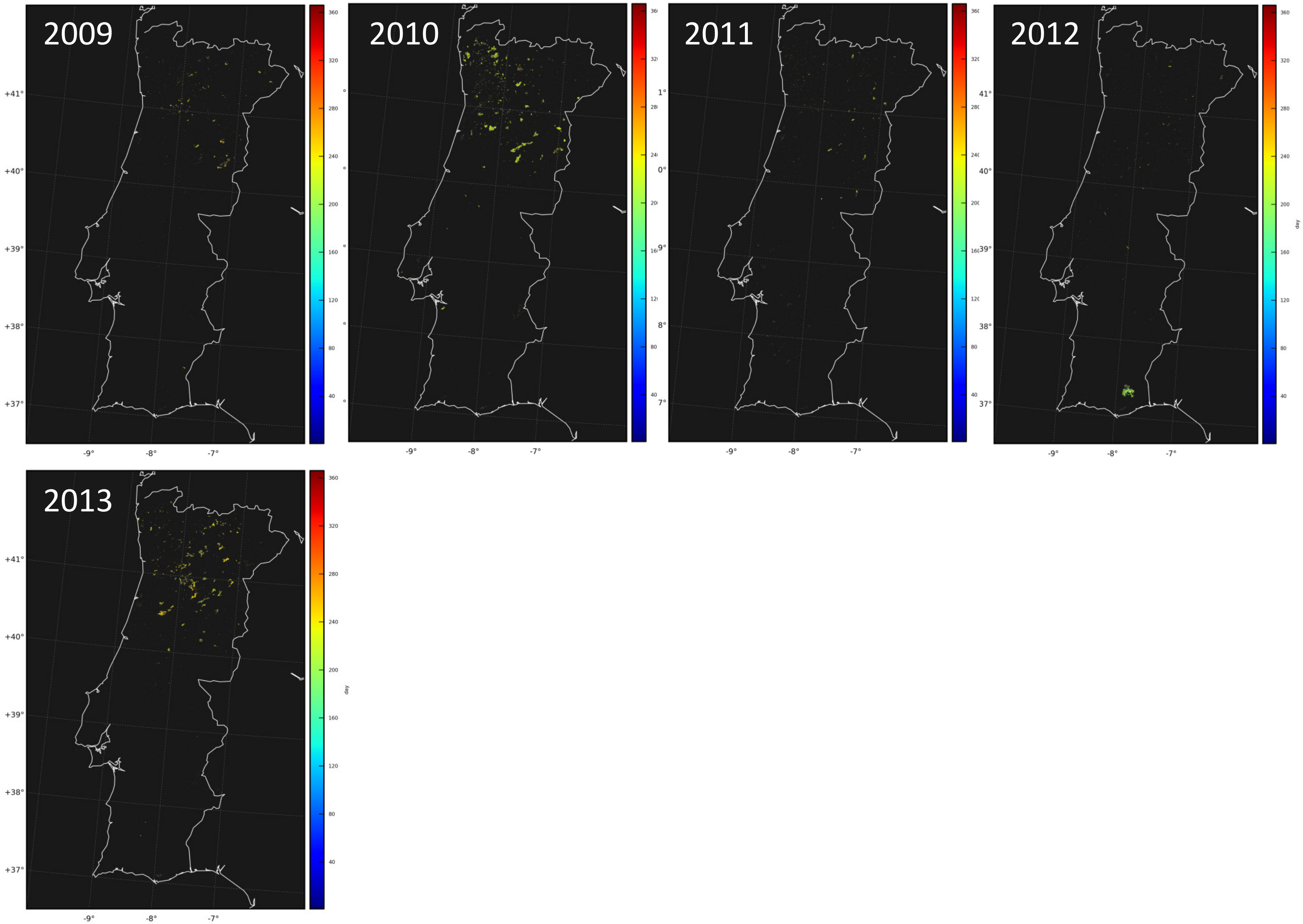

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Conclusions

- **The flexibility of the algorithm to bad data and atmospheric contamination.**

- **Easily adapted to other regions limited only by the availability and consistency of a time series of observations.**

Future work

•Explore the use of Object based classifications to the resulted date of the year maps

•Improve the optimization procedure and evaluate the cost function of the spatial revision

•Adjust parameters and apply to Mediterranean regions (not only in Europe but also in US, Australia, South America and Australia)

References

Benali A., Mota B., Pereira J.M.C., Oom D., Carvalhais N. "Global patterns of vegetation fire seasonality" In proceeding of European Geophysical Union General Assembly (2013)

Killick R., Paul F., I. A. Eckley I. A. "Optimal detection of changepoints with a linear computational cost." Journal of the American Statistical Association 107.500 (2012): 1590-1598.

Mota B., Pereira J.M.C., Campagnolo M., Killick R. "MODIS 250m burned area mapping based on an algorithm using change" (2013) In proceeding of European Geophysical Union General Assembly (2013)

Thank you